Global Journal of Pure and Applied Mathematics.
ISSN 0973-1768 Volume 12, Number 1 (2016), pp. 361-367

http://www.ripublication.com

ARAR Algorithm in Forecasting Electricity Load Demand in Malaysia

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Abstract

Electricity load demand has grown more than four-fold over the last 20 years period. The purpose of the current study is to evaluate the performance of ARAR model in forecasting electricity load demand in Malaysia. Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) will be used as a benchmark model since the model has been proven in many forecasting context. Using Root Mean Square Error (RMSE) as the forecasting performance measure, the study concludes that ARAR is more appropriate model.

Keywords: Load forecasting, ARAR, ARIMA

1 Introduction

ARAR algorithm is actually an adaptation of ARARMA algorithm which the idea is to apply selected memory-shortening transformation, and then fit an ARMA models to the transformed series [1]. ARAR algorithm is one of the useful forecasting techniques for a wide range of real data sets. However, the application of ARAR model in forecasting electricity load demand is still not widespread as compared to commonly used model, which is ARIMA based on literature.

Fong Lin Chu [2] studied ARAR models and its usefulness as a forecast generating mechanism for tourist demand for nine major tourist destinations in the Asia Pacific Region. The forecast of ARAR model was compared to Seasonal ARIMA (SARIMA) models. Based on RMSE and MAPE values, ARAR model can be deemed as credible alternative for forecasting in tourism demand area.

Mahendran Shitan and Yung Lerd Ng [3] forecasted the total fertility in Malaysia by using ARAR algorithm and ARIMA models. They found that ARAR model was the most appropriate models for forecasting fertility rate in Malaysia. XingliMeng [4] used Time Series models in modelling and forecasting hourly wind production in Sweden. She used spectral analysis, seasonal unit root and HEYG test, SARIMA and ARAR algorithm to the warm and cold season series. As a result, ARAR algorithm outperformed SARIMA models for warm season and for cold season, these two models have similar forecasting trends.

In this paper, ARAR algorithm will be used in forecasting Malaysian electricity load demand and its performance will be compared to ARIMA models.

2Methodology

ARAR Algorithm

The ARAR algorithm is basically the process that applied memory shortening transformation and fitting the autoregressive model to the transformed data. It is used to predict the future data from existing sequence data. The algorithm was introduced by Brockwell and Davis (2000) and it consists of three phases throughout the process.

Phase 1: Memory Shortening Process

This phase involves the process of transformation from a long-memory series to a short-memory series. This process continues until the transformed series is classified as short-memory and stationary. The algorithm for deciding among the long-memory (L), medium-memory (M) and Short-memory (S) can be described as follows:

1) For each $\tau = 1,2,\ldots,15$, $\gamma(\tau)$ is calculated and we choose the value that minimizes the equation (1) below,

$$\min \frac{\sum_{t=\tau+1}^{n} \left[Y_t - \gamma Y_{t-\tau}\right]^2}{\sum_{t=\tau+1}^{n} y_t^2} \quad (1)$$

2) In the case of $\tau > 2$ *and* $\gamma(\tau) \geq 0.93$, we use equation (2) below,

$$\hat{Y}_t = Y_t - \gamma_t Y_{t-\tau} \quad (2)$$

3) In the case of $\tau = 1$ *or* $\tau = 2$ *and* $\gamma(\tau) \geq 0.93$, we use equation (3) below,

$$\hat{Y}_t = Y_t - \gamma_1 Y_{t-1} - \gamma_2 Y_{t-2} \quad (3)$$

4) If $\gamma(\tau) \leq 0.93$, the series is short-memory.

After the shortening-memory transformation is achieved, the short-memory series is defined by,

$$\{S_t, t = k+1,..n\}$$

Phase 2: Fitting Autoregressive Model

The next step in this phase is to fit an autoregressive process to the mean corrected series,

$$X_t = S_t - \bar{S}, \quad t = k+1,..n$$

where $\bar{S}$ denoted by the sample mean of $S_{k+1},\ldots,S_n$. The Autoregressive model is fitted using the model (4) below,

$X_t = \gamma_1 X_{t-1} + \gamma_{l1} X_{t-l1} + \gamma_{l2} X_{t-l2} + \gamma_{l3} X_{t-l3} + \xi_t$ *where* $\xi_t \sim WN(0, \sigma^2)$

Note that the coefficient γ_k and white noise variance are calculated by using Yule-Walker's equation as shown below,

$$\begin{bmatrix} 1 & \hat{\rho}(l_1-1) & \hat{\rho}(l_2-1) & \hat{\rho}(l_3-1) \\ \hat{\rho}(l_1-1) & 1 & \hat{\rho}(l_2-l_1) & \hat{\rho}(l_3-l_1) \\ \hat{\rho}(l_2-1) & \hat{\rho}(l_2-l_1) & 1 & \hat{\rho}(l_3-l_2) \\ \hat{\rho}(l_3-1) & \hat{\rho}(l_3-l_1) & \hat{\rho}(l_3-l_2) & 1 \end{bmatrix} \begin{bmatrix} \gamma_1 \\ \gamma_{l1} \\ \gamma_{l2} \\ \gamma_{l3} \end{bmatrix} = \begin{bmatrix} \hat{\rho}(1) \\ \hat{\rho}(l_1) \\ \hat{\rho}(l_2) \\ \hat{\rho}(l_3) \end{bmatrix}$$

and $\sigma^2 = \hat{\psi}(0)[1 - \gamma_1\hat{\rho}(1) - \gamma_{l1}\hat{\rho}(l_1) - \gamma_{l2}\hat{\rho}(l_2) - \gamma_{l3}\hat{\rho}(l_3)$, where $\hat{\psi}(k)$ and $\hat{\rho}(k), k = 0,1,2,.....$,are the sample autocovariances and autocorrelations of the series $\{X_t\}$. For each l_1, l_2, l_3 such that $1 < l_1 < l_2 < l_3 \le m$, the coefficient γ_k can be computed by choosing m= 13 or 26.

Phase 3: Forecast

The last step in ARAR algorithm is to forecast using the combination between the equation obtained from phase 1 and phase 2. Phase 1 is the memory-shortening process and phase 2 is the fitting the autoregressive model to the mean corrected series. The memory-shortening filter obtain from the first phase can be expressed as :

$$S_t = \phi(B)Y_t = (1 + \phi_1 B + ... + \phi_k B^k)Y_t = Y_t + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + ... + \phi_k Y_{t-k} \quad (4)$$

Note that $\phi(B)$ is the polynomial in the backward shift operator.

The autoregressive models to the mean corrected series obtain from phase 2 can be expressed as:

$$\gamma(B)X_t = \xi_t \quad (5)$$

Where $\gamma(B) = 1 - \gamma_1 B - \gamma_{l1}(B^{l1}) - \gamma_{l2}(B^{l2}) - \gamma_{l3}(B^{l3})$

The ARAR Model is obtained by combining equations (4) and (5), such that :

$\varphi(B) = \gamma(B)\phi(B)$

$\varphi(B)Y_t = \gamma(1)\bar{S} + \xi_t \quad (6)$

The final model obtained in equation (6) is then used to forecast.

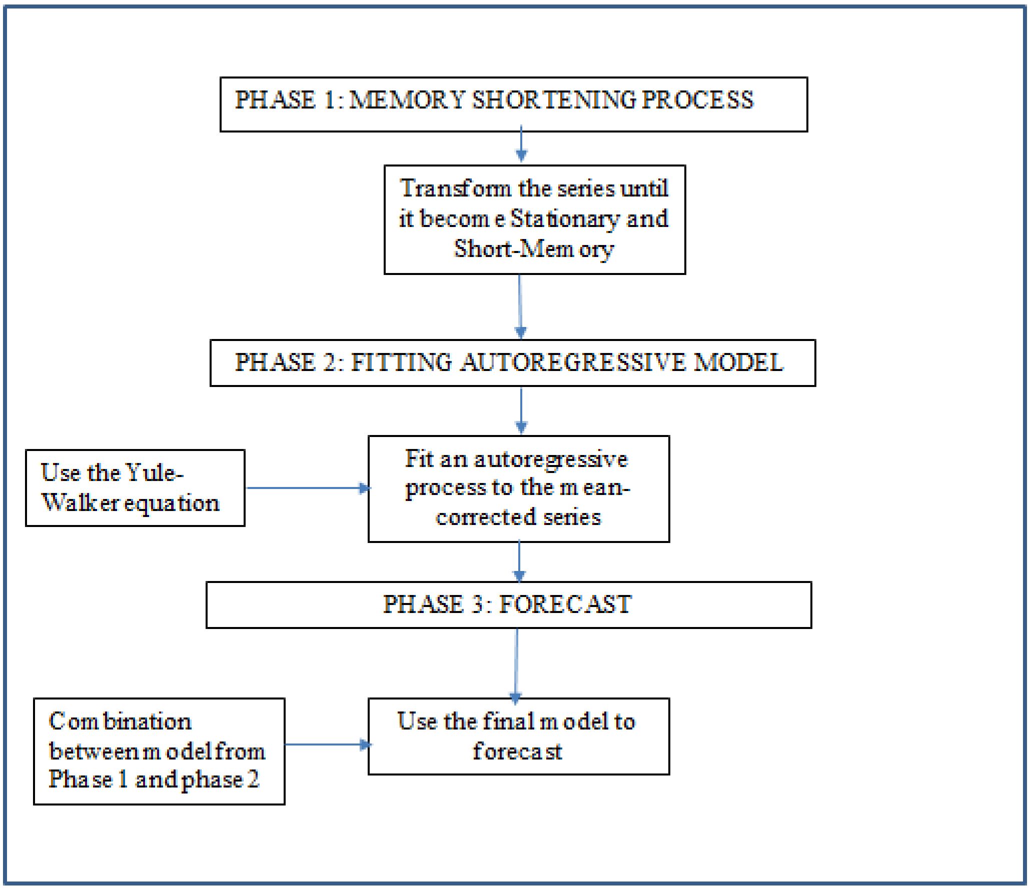

Figure 1: ARAR Algorithm process

Forecast Accuracy Criteria

The most adequate model for ARIMA forecasting which has been set as a benchmark for this study will be compared with ARAR model using the forecasting accuracy criteria. RMSE has been selected to be one of the powerful forecast accuracy criteria which are given by the following equation

$$RMSE = \sqrt{\frac{\sum_{n}^{t}(y_t - \hat{y}_t)^2}{n}}$$

Where y_t and $\hat{y}_t$ are the actual observe value and the predicted values, resectively, while n is the number of predicted value.

3Results and Discussion

Figure 2 shows the linear trend analysis for the original electricity load demand data.The plot suggests that the original data set is not stationary. Therefore, the first difference $\Delta y = y_t - \hat{y}_t$ is applied to the original data.

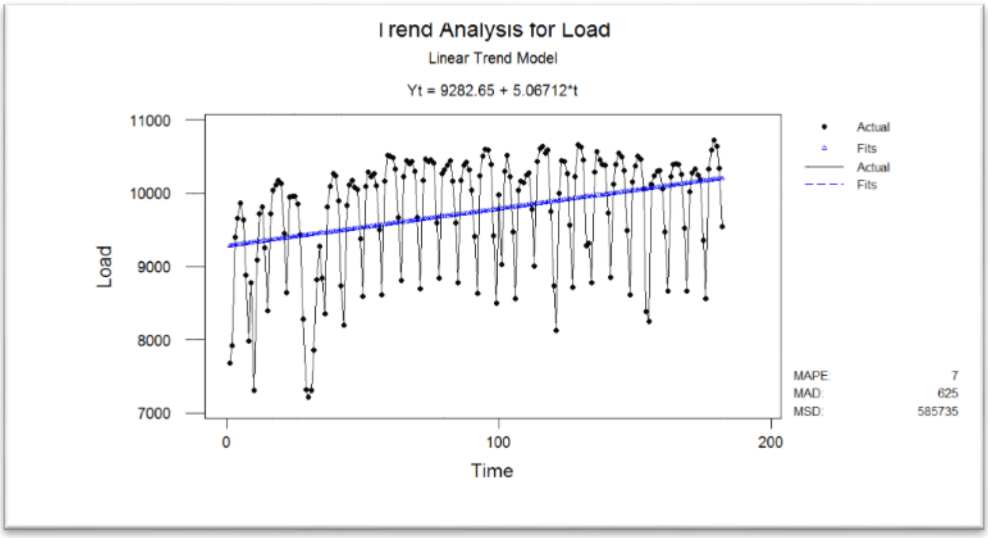

Figure 2: Linear Trend Analysis of the original data.

After the series is stationary, then we apply the second step for ARAR algorithm which is fitting autoregressive model. R statistical software has been used to analyze the data. Based on the result from the software, it is suggests thatthe optimal lags for the fitted model are 1, 7, 14 and 21. After that, the fitted model is used to forecast the data. Here, we set to forecast up to 10 step head. The forecasting graph and result are shown in Figure 3 and Table 2 respectively.

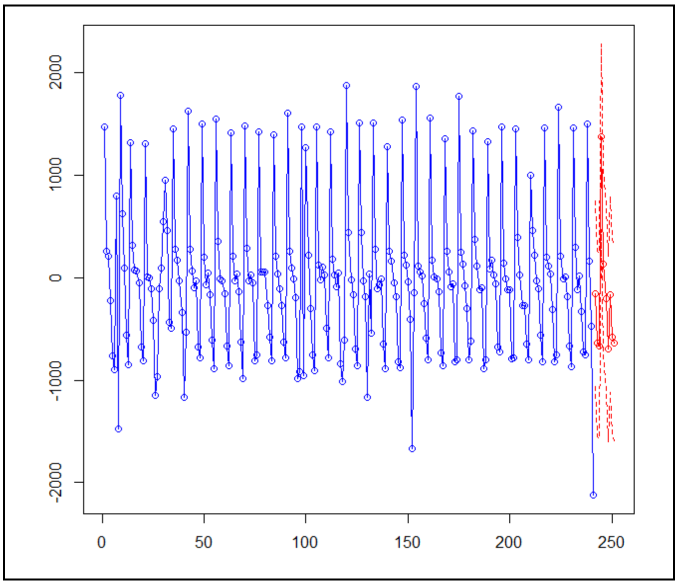

Figure 3: Forecasting plot for the first difference data using ARAR algorithm

ARIMA models were setup as the benchmarks for this study. Based on the plot and the significant spike, the following nine models have been estimated and identified using R statistical software. The potential models are shown in Table 1 below.

Table 1: The list of the potential ARIMA models

MODEL	AIC	RMSE	MODEL	AIC	RMSE
ARIMA(2, 1, 2)	15.81060	637.9573	ARIMA(3, 1, 4)	15.68860	590.0231
ARIMA(2, 1, 3)	15.76337	619.5779	ARIMA(4, 1, 2)	15.73980	608.6154
ARIMA(2, 1, 4)	15.75109	612.3372	ARIMA(4, 1, 3)	15.74896	607.9474
ARIMA(3, 1, 2)	15.77827	624.0926	ARIMA(4, 1, 4)	15.68240	584.7161
ARIMA(3, 1, 3)	15.74956	611.7324			

The estimated ARIMA model for forecasting the electrical load with their corresponding AIC values is given in Table 1. It is shown that the ARIMA (4, 1, 4) has the minimum AIC and RMSE values. It is shown that ARIMA (4, 1, 4) is best model modelling and forecasting among the other ARIMA models

Comparative Performance for ARAR and ARIMA Models

RMSE will be used as a forecast accuracy criterion in order to measure the performance of the best models from ARAR and ARIMA models. The RMSE values are tabulated in Table 2.

Table 2: Comparative performance for ARAR and ARIMA models.

BEST FORECASTING MODELS	RMSE
ARAR	462.1843
ARIMA(4, 1, 4)	584.7161

From Table 2, the lowest RMSE values are from ARAR model. Hence, ARAR models are the best models for modelling and forecasting electricity load demand data in Malaysia as compared to ARIMA models.

4Conclusion

The forecasting of electricity load demand has become one of the major fields of research in recent years. This paper presents an attempt to forecast the load demand by using ARAR models. ARIMA models have been selected as benchmark since the models has been extensively used in many areas in time series, especially for load forecasting. ARAR has been considered as the best model as compared to ARIMA model due to the lowest RMSE value. This model can be used in forecasting the electricity load demand in Malaysia for the future..

Acknowledgements
The main author would like to acknowledge the support of the Faculty of Engineering Technology (FTK), Universiti Teknikal Malaysia Melaka (UTeM).

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